The Propensity to Cycle Tool: An open source online system for sustainable transport planning

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1 Abstract

Encouraging cycling, as part of a wider sustainable mobility strategy, is an increasingly common objective in transport planning institutions worldwide. Emerging evidence shows that providing appropriate high-quality infrastructure can boost local cycling rates. To maximize the benefits and cost-effectiveness of new infrastructure, it is important to build in the right places. Cycle paths, for example, will have the greatest impact if they are constructed along 'desire lines' of greatest latent demand. The Propensity to Cycle Tool (PCT) seeks to inform such decisions by providing an evidence-based support tool that models current and potential future distributions and volumes of cycling across cities and regions. This paper describes this model and its application to case study cities in England. Origin-destination (OD) data, combined with quantitative information at the level of administrative zones, form the basis of the model, which estimates cycling potential as a function of route distance, hilliness and other factors at the OD and area level. Multiple scenarios were generated and interactively displayed. These were: 'Government Target', in which the rate of cycling doubles in England; 'Gender Equality', in which women cycle as much as men; 'Go Dutch', in which English people cycle as much as people in the Netherlands; and 'E-bikes', an exploratory analysis of increasing the distance people are willing to cycle due to new technology. The model is freely available online and can be accessed at geo8.webarch.net/master/. This paper also explains how the PCT's open source approach allows it to be deployed in new cities and countries. We conclude that the method ~~presented has potential to assist with planning for cycling-dominated cities worldwide~~can help plan for modal shift to active travel, which can in turn improve citizen health and assist with the global transition away from fossil fuels.

2 Introduction

Cycling can play an important role in ~~making transport systems more~~ creating sustainable, healthy and equitable ~~. This mode of transport~~ transport systems. Cycling already provides fast, affordable, and convenient mobility to millions of people each day (Komanoff, 2004). Mounting evidence of the external costs ~~associated with car-dominated~~ of car-based transport systems (Han and Hayashi, 2008; Mizutani et al., 2011; Newman and Kenworthy, 1999; Shergold et al., 2012) and the benefits of cycling (De Nazelle et al., 2011; Oja et al., 2011; Woodcock et al., 2013) has pushed cycling up the transport agenda in recent years. Cycling is increasingly central to sustainable transport strategies, as illustrated, for example, by funding for cycling policies worldwide[1] and the ~~global~~ proliferation of publicly subsidized 'bike share' schemes at the city level (O'Brien et al., 2014).[2]

[1]Several examples of multi-million Euro projects are provided by the European Cyclist' Federation, the FIA Foundation and the World Cycling Atlas. There has been little academic research on the proportion of transport budgets allocated to cycling worldwide, hence the use of resources from NGOs here.

[2]An interactive web map associated with O'Brien et al. (2014) illustrates the distribution of many of the largest bike share schemes worldwide. See bikes.oobrien.com.

Emerging evidence illustrates that high-quality infrastructure is an effective way of promoting cycling as a safe, accessible and convenient transport option for people of all ages and abilities (Heinen et al., 2015). Thanks to various designs of modified cycles (e.g. quadricycles and handcycles), cycling can also provide an efficient means of self propulsion for people who would have to depend on motorised modes or other people (Aldred and Woodcock, 2008).

Within this fast-moving policy context, the question of where to construct new cycle infrastructure is of strategic importance (Larsen et al., 2013). In response, professional transport planners and consultancies have developed new methods for identifying cost-effective infrastructure interventions, such as Aecom's proprietary Permeability Assessment Tool (Payne, 2014). Yet geographically specific prioritisation of new infrastructure is seldom raised in academic research on cycling and active travel more widely. The design (Heath et al., 2006; Transport for London, 2014; Welsh Government, 2014) and geographic location (Aultman-Hall et al., 1997; Minikel, 2012) of cycle paths are important factors influencing the attractiveness of cycling and the rate of cycling (Pucher et al., 2010). Through the case study of the PCT, this paper explores the ability of strategic transport planning support tools to assist the decision-making process so that cycling investment is spent effectively.

The Propensity to Cycle Tool (PCT) is an interactive map-based 'planning support system' (Geertman and Stillwell, 2009). As with other previously documented online systems (e.g. Sinnott et al., 2014), the PCT provides a range of information to the user to inform evidence-based policy (Pettit et al., 2013). The PCT differs from previous planning support systems, in its:

- Focus on future scenarios of cycling.
- Estimation and visualisation of information at the zone and 'desire line' level.
- Route-allocation of cycling 'desire lines' from origin destination data ('OD pairs'), enabling specific routes to be identified for improvement.

The PCT was commissioned by the UK's Department for Transport to identify "parts of the country [England] with the greatest propensity to cycle" to help prioritise strategic investment in active travel (Department for Transport, 2015). Part of the contract involved user testing sessions. Feedback from over 70 practitioners and policy-makers provided: (i) confirmation of the tool's utility for decision-making; (ii) input into the tool's user interface; and (iii) ideas for future development.

The PCT is the first online and interactive planning support system to focus explicitly on cycling. The computer code underlying the PCT is open source, enabling the methods described in this paper to be reproduced. With access to appropriate data (described in the next section) and R programming skills, the PCT can be deployed in new contexts. The codebase underlying the PCT is publicly available at github.com/npct under the conditions of the MIT license. The aggregate level OD model underlying the PCT was written in R (R Core Team, 2015). The interface was written in **shiny**, an R package for creating online web applications for data visualisation (Chang et al., 2015).

The PCT is a *strategic* transport planning tool. Its policy-relevance stems from its ability to develop, compare and visualise various scenarios for cycling futures at city to national levels. Unlike 'microscopic' transport models such as SUMO and PTV VISSIM, which simulate vehicular traffic in real time (Behrisch et al., 2014; Krajzewicz et al., 2014), the PCT is scalable to the national level. The PCT is also able to estimate cycling potential at relatively fine-grained (and flexible) levels of geographic resolution.

Unlike McCollum and Yang (2009) and other national-level scenario-based approaches, the PCT allows estimation of where new cycling trips are most likely to be generated given predetermined overall increases in cycling. This makes the tool especially well-suited to local-level analysis of the impacts of achieving a target level of cycling (typically measured as a proportion of all trips). For example, our 'Government target' scenario assumes a doubling in the level of cycling in England (DfT 2014). The PCT provides a method to answer the question: if cycling increases by 'x' nationally or regionally, how much is cycling likely to increase locally? More specifically: along which routes would the new cycle trips plausibly occur?

This ability to model propensity to cycle at the OD level is one important, and novel, feature of the PCT. An 'OD pair' in this context can be represented visually as a 'desire line'. This is a straight line connecting the origin (O) with the destination (D) (Chan and Suja, 2003). These concepts are related to the common T_{ij} matrix notation in transport modelling, which represent the number of trips between OD pairs (Ortúzar and Willumsen, 2001; Simini et al., 2012). The model simulates the proportion trips made by cycle between OD pairs, enabling visualisation of cycling 'desire lines', whereas previous approaches to modelling cycling potential have tended to focus only on area-based measures. Parkin et al. (2008), for example, used a multiple regression model to estimate levels of commuter cycling at an area level. Similarly local survey data has been used to identify areas with high numbers of 'potentially cyclable trips' in London (Transport for London, 2010). However, neither analysis identified the travel corridors along which these simulated cycle trips would be made.

More localised approaches, which use information about the route network and the trajectories of cyclists using GPS data, also have great potential for creating an evidence-base for prioritising investment in cycle paths locally (Broach et al., 2012; Ehrgott et al., 2012). However, a key limitation of many models is that the results are not presented in a form that is dynamic or accessible to transport planners. By allocating the results of an individual-level regression model to the route network, a method presented by Zhang et al. (2014) was able to prioritise routes to "achieve maximum impacts early on". The PCT differs by operating at the OD level for scalability.

Results for each scenario are pre-calculated, enabling the outcome to be displayed rapidly; calculating the results 'on-fly' would lead to an unresponsive interface. The user is not required to specify any numerical parameters to interact with the PCT. The only software needed for users to run the PCT is a web browser, reducing a key technological barrier to transport planning. The PCT's open source approach reduces two additional barriers to effective use of transport planning software: cost and access to source code. The PCT is part of a wider trend in transport research towards greater transparency in software development and collaboration (Novosel et al., 2015; Tamminga et al., 2012). This open source approach, combined with the widespread availability of OD data (as discussed in the next section), should make the PCT easy to deploy in new contexts.

3 Data

The PCT relies on two key input datasets:

- *Origin-destination* (OD) data relating the number of trips taking place between administrative zones. These can be represented as straight 'desire lines' or allocated to the route network.
- *Geographical data* providing the coordinates of trip origins and destinations.

The OD model described in this paper can work for anywhere that has access to such data. Hilliness and route network distance were also included in the regression model. To link the OD and geographic datasets together, *zone ids* are needed in both datasets. An R package, **stplanr**, was developed for this purpose and other data manipulation challenges.

Tables 1 and 2 illustrate the two input datasets. Fig. 1 shows the output, straight lines with attributes for each OD pair in both directions. These are also referred to as 'desire lines' when represented as straight lines on the map (Chan and Suja, 2003; see Tobler, 1987). The visualisation of the OD data builds on published work on cartographic visualisation (Rae, 2009; Wood et al., 2010). The model for England described in this paper uses the following open datasets (similar OD datasets are available for cities across the world):

- OD data representing the number of trips between origin destination pairs, disaggregated by mode of travel. We used the file `wu03ew_v2.csv`, obtained from the UK Data Service (see Table 2 for a sample of this dataset)[3] This dataset is from the English Census 2011 on travel to work. Note the origin and destination codes in some rows are the same, indicating *intra-zone* travel.

[3]See wicid.ukdataservice.ac.uk/cider/wicid/downloads.php.

- The population-weighted centroids of local administrative zones (see Table 1). We used 'Medium Super Output Areas' (MSOAs), with an average population of around 7,800 people, as the zonal system for both origins and destinations. MSOAs were the highest geographical resolution at which the mode-specific OD data were available. MSOA zone boundaries were provided under the UK's Open Government Licence.[4]
- Route distance, assigned to each desire line using the CycleStreets.net API.[5]
- Hilliness of zones and routes. There are various ways to generate this data, ranging from the simple (e.g. vertical displacement between origin and destination) to the complex (e.g. total amount of climb along the route network in both directions). We calculated mean gradient per MSOA zone using publicly available digital elevation model (DEM) data supplied by NASA.[6]

Table 1: Sample of the OD input dataset, representing the number of people who commute from locations within and between administrative zones (MSOAs)

id	Area.of.residence	Area.of.workplace	All	Bicycle
920573	E02002361	E02002361	109	2
920575	E02002361	E02002363	38	0
920578	E02002361	E02002367	10	0
920582	E02002361	E02002371	44	3
920587	E02002361	E02002377	34	0
920591	E02002361	E02002382	7	0

Table 2: Sample of the 'cents' input dataset, representing the geographical location of the population-weighted centroids of MSOA zones described in Table 1.

	geo_code	MSOA11NM	coords.x1	coords.x2
1708	E02002384	Leeds 055	-1.546463	53.80952
1712	E02002382	Leeds 053	-1.511861	53.81161
1805	E02002393	Leeds 064	-1.524205	53.80410

We used the Census 2011 travel to work dataset for its comprehensive coverage of the population, high geographic resolution and assurances surrounding data quality.

A variety of emerging sources can also provide OD data, including 'Big Data' from commercial companies. These alternative sources of OD data include: mobile telephone service providers (Smoreda et al., 2013); public transport data (Kitchin, 2013); household travel surveys (Transport for NSW, 2014); geolocated social media (Stefanidis et al., 2011).

[4]See data.gov.uk/dataset/lower-layer-super-output-areas-ew-2011-population-weighted-centroids.

[5]To implement this functionality in a generalisable way a custom function, `route_cyclestreet()`, was written for the R package **stplanr**.

[6]See srtm.csi.cgiar.org/ for the data and the steepness.R file in the project's repository for the processing algorithm used. "Version 4" of the dataset was used. To allocate this area-based hilliness metric to OD pairs, we calculated the average hilliness of origin and destination zones. This method has the disadvantage that accuracy decreases with increased trip distance.

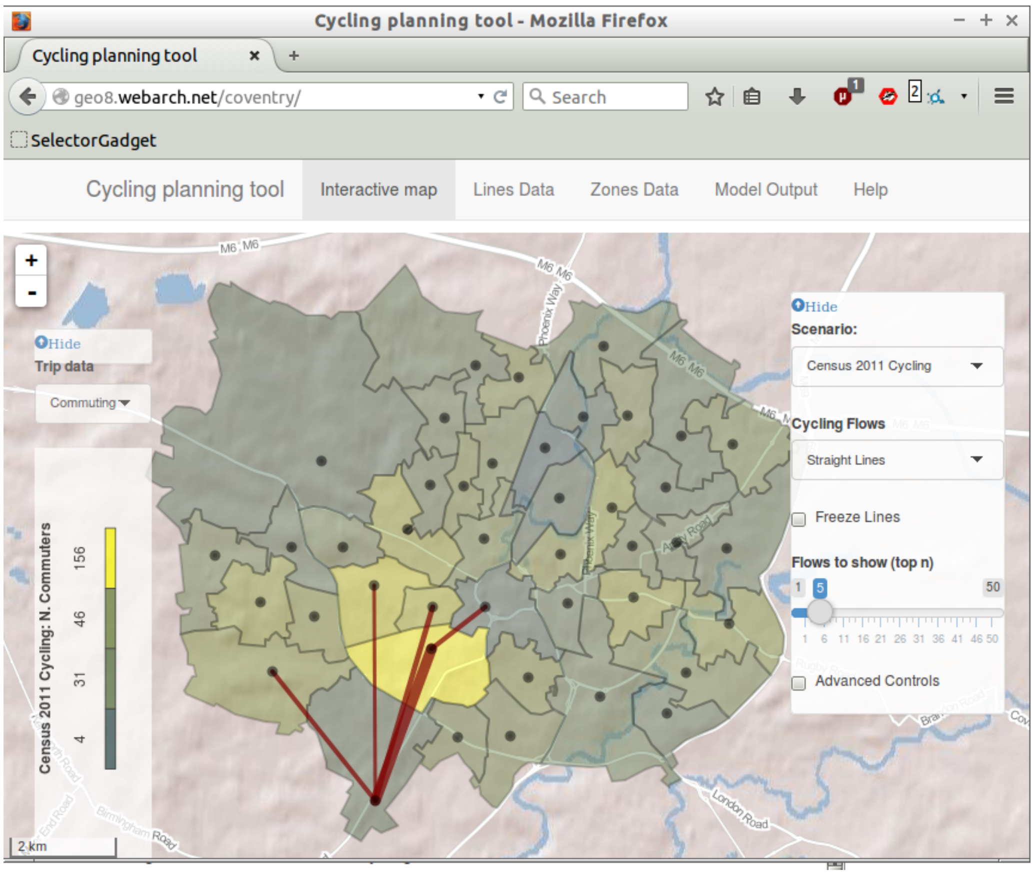

Figure 1: Overview of the PCT map interface. The lines represent trips between origin and destination pairs for Coventry. Width represents the total number of trips. Note the use of population-weighted (as opposed to geographic) centroids for the point of departure and destination.

4 Data manipulation and modelling

4.1 Geographic data

To ensure reproducibility and enable deployment of the model outside the original case study cities, a systematic data loading method was developed. The computational work to load the various datasets was developed in a series of modular scripts that were subsequently integrated into a single script: `load.Rmd`. This approach ensures that each component of the data (e.g. OD data, administrative zones, topography data) can be loaded separately with a single 'master' script to bring together the diverse data sources.[7]

Instead of running the model for the entirety of England, the loading script, OD model and output visualisations were run on a region-by-region basis. This was to prevent overloading the computer with national data and to focus attention on the level at which funding is allocated. Using only one regional geographic level could, however, reduce emphasis on 'edge zones' that straddle two or more regions. To overcome this issue it is worth considering using more than one regional geographical system. A modified version of the model could be run at the national level. Another solution to the problem of 'edge zones' is to create buffers around the regions (as discussed below).

The data above were loaded on a region-by-region basis, not for the entire country at once. This was partly because transport decisions (such as where to build new cycle routes) tend to be made at the local level (Gaffron, 2003) and partly to reduce the computational requirements (particularly use of RAM) for scalability. In many cases the choice of region to use is not straightforward, however. This is shown in Fig. 2, which illustrates the decision that must be made between larger and smaller regional units.

4.2 Variable zone and OD pair selection criteria

Flows assigned to the transport network were generated when OD pairs were mapped onto the current travel network. This network-level data generation was undertaken by CycleStreets.net (a routing service for planning cycle trips), constituting the most computationally intensive part of the model.

To reduce data processing and visualisation times a sub-sample of OD pairs was used. The aim was to reduce the number of OD pairs whilst retaining the overall travel pattern. To do this a minimum number (labelled `mflow`) of trips between OD pairs was specified. OD pairs with less than `mflow` trips were removed from the analysis. This followed the insight that the distribution of number of commuters per OD pair is skewed: a relatively small number of OD pairs along major travel corridors account for a disproportionately high proportion of travel. In the City of Manchester, for example, setting `mflow` to 30 reduced the number of OD pairs by 85%, yet still accounted for almost 70% of commuters. Different values for `mflow` were tested to reach a reasonable balance between comprehensive coverage and speed of saving and loading data. Another way to subset OD pairs is to set the maximum Euclidean (or "crow-flies") distance between OD pairs (labelled `mdist`). We tested various values for `mdist` and settled on 15 km. This translates to around 20 km on the route network assuming a *circuity* (Iacono et al., 2010) value of 1.3. From the Great Britain National Travel Survey, only 1.1% of cycle commutes in Britain exceed this distance.

4.3 The regression model

Once the input data (discussed in the previous section) has been processed and sub-setted to the area of interest, it is passed to a regression model.

For all scenarios except *gender equality*, a regression model was used to estimate the potential rate of cycling at the OD level. It does so using Ordinary Least Squares (OLS) to optimize a number of model parameters linking distance (d) and hilliness (H) to the *dependent variable*: the proportion of trips made per OD pair (*pcycle*). The concept of 'distance decay' (Martínez and Viegas, 2013) was used in the model to describe the

[7] See github.com/npct/pct/tree/master/loading-data for a full list of the loading scripts used for the PCT.

Figure 2: The regional units used to iteratively load the geographical data. These were English Local Authority Districts (LADs, above) and County and Unitary Authorities (CUAs, below) levels of transport planning.

(non-linear) relationship between the route distance of OD pairs and the proportion of trips made by cycling. Euclidean distance could be used in contexts where route distance is not known.

It is well-known that *pcycle* tends to decrease with increasing distance (Iacono et al., 2010). Based on this work and exploratory analysis of the data we estimated the *log* of *pcycle* rather than *pcycle* directly. Hilliness was included as a continuous variable in our model and was expected to have a linear impact on *pcycle*. The formula chosen was:

(1)

$$log(pcycle) = \alpha + \beta_1 d + \beta_2 d^{0.5} + \gamma H$$

where d is distance (km, route distance between population weighted centroids) and H is the hilliness (average angular degrees of origin and destination zones) per OD pair. The remaining values are scalar coefficients to be estimated. α represents the intercept (the rate of cycling very short trips). β_1 (which must be negative for *pcycle* to tend to zero as distance tends to infinity) and β_2 represent the rate of distance decay. γ represents the impact of hilliness on cycling. A 'quasipoisson' general linear model was used to implement this formula using the base R function `glm`, which predicts *log*(*pcycle*) to account for the aforementioned exponential decay.

4.4 Zone Buffer

Running the PCT region-by-region means ignoring all the MSOA zones outside the region. If the region is a self-contained transport system this will not create problems. If the region is part of a larger conurbation, however, the clipping could be problematic. To solve this problem we created buffer zones around each region, from which additional zones were sampled in regions in which the number of MSOA zones fell below some threshold, chosen to be 60. For example, this meant that additional zones were selected outside the City of Manchester, which has 57 MSOAs (see Fig. 7 below). This protocol increased the sample size by including all zones whose population-weighted centroid lies inside the buffer, the width of which can also be pre-specified.

4.5 The Model Output tab

Users can view a summary of the model via the 'Model Output' tab (Fig. 3). The tab was added in response to feedback during the user testing sessions. The output tab communicates the results of the model, including key statistics, diagnostic plots and model-results on a per-region basis. This means that a different summary document is provided depending on which local authority the user is currently exploring.

5 Model scenarios

Scenarios were developed to indicate how local cycle use could increase. Current constraints to cycling, including the aforementioned factors of distance and hilliness, can to some degree be overcome by new technology (see the *ebike* scenario below).

The four scenarios developed for the case study cities were developed to explore different cycling futures in England. Because time-scales are not specified, they are not necessarily mutually exclusive.

- Government target (*govtarget*). This scenario represents a doubling of the number of cycling trips in England. Although this is a substantial increase in relative terms, cycle use still remains low in this scenario compared with countries such as the Netherlands, rising from 3% to 6% of commutes. *govtarget* allows for different rates of growth in different places. Above-average percentage increases (i.e. more than a doubling) are projected in areas with many short (i.e. potentially cyclable) trips and a low current rate of cycling. Conversely, areas with higher cycle use and a low proportion of short

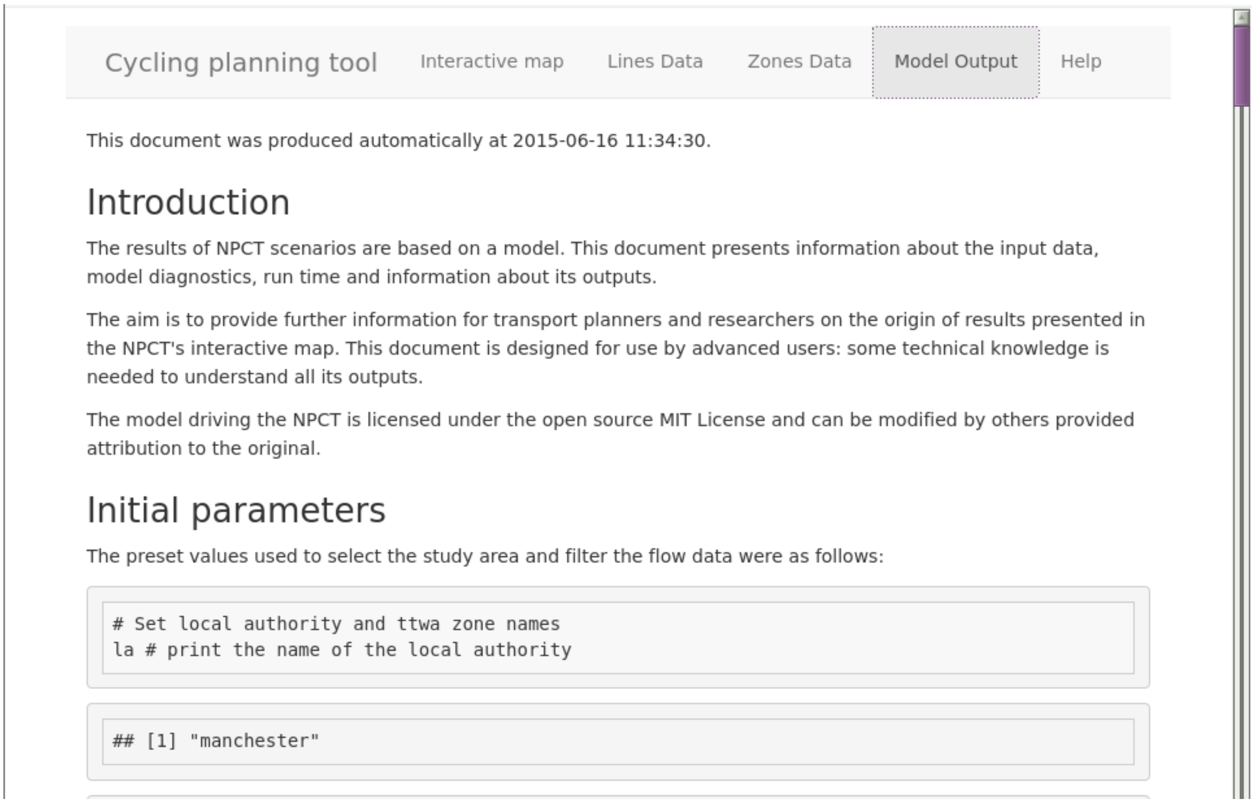

Figure 3: The Output Tab of the Propensity to Cycle Tool

commutes will have below-average growth. *govtarget* represents a slight reduction (but not elimination) of the localised infrastructural or cultural constraints which deter cycle use more in some places than in others. It therefore indicates where investment in increased cycle use might achieve the greatest impact in the short term.

- Gender Equality (*gendereq*). This scenario illustrates the increase in cycling that would result if women cycled as much as men, all other variables being equal. Specifically, the scenario sets the proportion of female cycle commuters to the current proportion of males in each OD pair. The scenario is based on the observation that in places where cycling is the norm, women cycle at least as much as men (Pucher et al 2010). *gendereq* thus represents the elimination of one specific cultural constraint. This scenario has greatest relative impact in areas where the rate of cycling is highly gender-unequal (Fig. 4). In absolute terms, cycling increases most in this scenario where cycling is already a common mode of transport.

- Go Dutch (*godutch*). While *govtarget* and *gendereq* build on current cycling behaviour, the *godutch* scenario focuses on long-term potential. The 'Go Dutch' scenario models what would happen if English people were as likely to cycle for a given trip (i.e. of the same distance and hilliness) as Dutch people, by applying Dutch distance decay curves to English travel patterns. The scenario represents the elimination of the infrastructural and cultural constraints which currently hold back cycle use in England, including all localised differences. So, unlike the *govtarget* and *gendereq* scenarios, the predicted levels of cycle use in *godutch* are unrelated to current levels, and are constrained only by local trip distance distributions and hilliness.

- E-bikes (*ebikes*). This scenario models the additional increase in cycle use that would be achieved through the widespread uptake of electric cycles ('E-bikes'). E-bikes enable longer journeys and make cycling a more viable option for a number of people, including those with low fitness and people with impaired mobility. This scenario is based on the Go Dutch scenario.

These scenarios are described more fully below. They are not intended to be definitive scenarios of cycling futures in England or anywhere else; we encourage users of the PCT to develop new scenarios relevant to new contexts.

5.1 Government Target

The Government Target scenario (*govtarget*) is based on the UK government's proposed target (as set out in its draft Cycling Delivery Plan (Department for Transport, 2014)) to double cycling in England, from 0.8 billion stages currently to 1.6 billion stages by 2025. However Department for Transport (2014) says nothing about where these additional trips would come from. The *govtarget* scenario is therefore based on our own assumptions about this. It aims to assist transport planners in identifying where new demand for cycling is likely to be greatest in the near term.

The key point about this scenario is that cycling does not double in all areas. Instead, the increase is related to the current commuter trips and the trip distance.

At the heart of the *govtarget* scenario is the previously discussed regression model (labelled *natmod*) estimating the dependent variable (*pcycle*). The new rate of cycling ($pcycle(govtarget)$) is the current rate of cycling plus this model-based estimate:

(2)
$$pcycle(govtarget)_{ij} = (pcycle_{ij} + pcycle(natmod)_d)$$

where $pcycle_{ij}$ is the 2011 Census proportion of commuters who cycle for an OD pair ij of distance d apart and $pcycle(natmod)_d$ is the proportion of commuters expected to cycle the distance d based on the national-level regression model. The sum of these values can be multiplied by the total number of commuters for all modes $tflow_{ij}$ to convert the proportion into a number of cyclists, i.e.:

(3)
$$SLC(govtarget)_{ij} = (pcycle_{ij} + pcycle(natmod)_d) * tflow_{ij}$$

where $SLC(govtarget)_{ij}$ is the *Scenario-based Level of Cycling* for this scenario for the ij OD pair. An example of this scenario for an imaginary OD pair *ab* with Euclidean distance 4.5 km is as follows. Based on a representative sample of OD pairs in the UK and under the 'national doubling', assume an additional 5% of commuters now cycle for all trips of 4.5km — i.e. $pcycle(natmod)_{4.5} = 0.05$. For our OD pair *ab* in the Census there are 200 commuters of which 2 are cyclists, $pcycle_{ab} = 0.01$. Applying the scenario adds an additional 5% of commuters which represents an additional 10 cyclists, far more than doubling. The same methodology is applied to all distances represented in the OD matrix.

The approach assumes that cycling potential against a given national increase is always a positive number. The larger the increase in cycling for the scenario, the less the current level matters. By contrast, the larger the current rate of cycling, the lower the impact this scenario has on the future rate of cycling.

Our implementation of the *govtarget* scenario is thus in line with findings from Sloman et al. (2014) and Heinen et al. (2015), who found that it is initially easier to achieve growth in cycle use in places where cycling is already common. However, with sustained investment in overcoming the infrastructural and cultural constraints which limit cycle use, there is great long-term potential for increased cycling in many areas that currently have a low rate of cycling. This is modelled in the Go Dutch scenario (described after the *gendereq* scenario).

5.2 Gender equality

The next scenario to be discussed is Gender Equality (*gendereq*). In this scenario cycling tends to grow more in areas that already have a high rate of cycling. The scenario recognizes that this disparity is reduced or absent in countries with a high rate of cycling (Fishman et al., 2015). The Gender Equality scenario (*gendereq*) builds on such insights and is based *observed level of cycling* (OLC) from the 2011 Census.

On average in England around 3/4 of cycle commuters are male, although this varies geographically (Aldred et al., 2015). *gendereq* assumes that gender equality is reached in cycling. A prerequisite is a model-based estimate of the number of male and female cyclists between origin and destinations for the observed data. This involves splitting the number of cyclists project by the model, the *Scenario-based Level of Cycling*, into male ($SLC(gendereq)_m$) and female ($SLC(gendereq)_f$) components:

(4)
$$SLC(gendereq) = SLC(gendereq)_m + SLC(gendereq)_f$$

More males cycle to work than females in every Local Authority in England (Fig. 4). For this reason, the *gendereq* scenario is based on the assumption that the rate of cycling amongst females increases to match the rate of cycling amongst males. Under *gendereq* $SLC(gendereq)_m = OLC_m$, there are no additional male cyclists. Note that this is not as simple as $SLC(gendereq)_f = SLC(gendereq)_m$, as the absolute number of female and male cyclists will also depend on the gender split of the total commuting population within each OD pair.[8] It is the *proportion* of males and females per OD pair who cycle that becomes equal, as follows.

(5)
$$pcycle(gendereq)_f = pcycle_m$$

(6)
$$\frac{SLC(gendereq)_f}{tflow_f} = \frac{OLC_m}{tflow_m}$$

(7)
$$SLC(gendereq)_f = tflow_f * \frac{OLC_m}{tflow_m}$$

OLC_m is the observed number of male cycle commuters (in the 2011 Census in this case), $SLC(gendereq)_f$ is number of female cycle commuters in the gender equality scenario, and $tflow_m$ and $tflow_f$ are the total numbers of males and females in the OD pair respectively.

$tflow_m$ and $tflow_f$ are both available at the OD level in the 2011 Census, as is the total number of cyclists (OLC). The proportion of cyclists who are male in each OD pair ($pmale_(cyclist)$) is not available in the published 2011 datasets. The smallest level at which the gender breakdown of cyclists is currently available is the zone level ('$pmale_{cyclist}(zone)$'), and we assume that all OD pairs have this same proportion of male cyclists. This allows the estimation the number of male cycle commuters as $OLC_m = OLC * pmale_{cyclist}(zone)$, so that

(8)
$$SLC(gendereq)_f = OLC * pmale_{cyclist}(zone) * \frac{tflow_f}{tflow_m}$$

and therefore the total number of trips for gender equality $SLC(gendereq)$ would be

[8] To illustrate this point, consider an OD pair in which the total number of female commuters is larger than the total number of male commuters. In this case, the number of female cyclists would exceed the number of male cyclists in the *gendereq* scenario.

(9)

$$SLC(gendereq) = OLC_m + SLC(gendereq)_f$$

(10)

$$SLC(gendereq) = OLC * pmale_{cyclist}(zone) * (1 + \frac{tflow_f}{tflow_m})$$

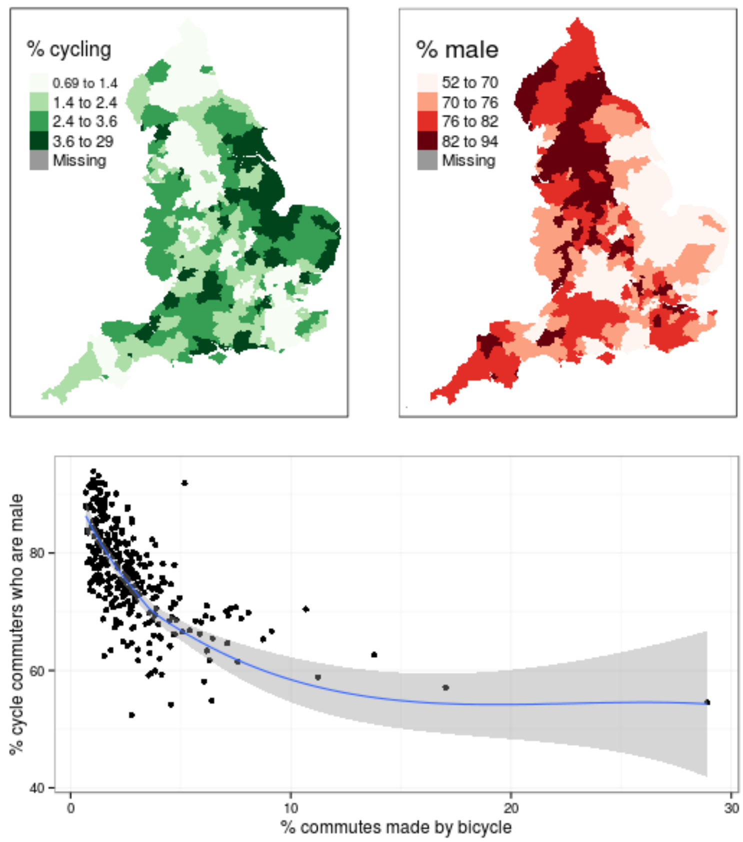

Figure 4: Cycling and the gender balance of cycling in England. The choropleth maps illustrate the spatial distribution of the two variables. The scatter plot illustrates the relationship between the two variables cycle commuting (x axis) against the proportion of commuter cyclists who are male (y axis) for all 326 Local Authorities (including Districts) in the UK.

To illustrate how this method works in practice, imagine an OD pair in which 50 from a total of 500 people commute by cycle ($tflow = 500; OLC = 50$). 300 of the total trips in the OD pair are made by males ($tflow_m = 300$) and 200 by females ($tflow_f = 200$). In addition, 70% of commuter cycling in the wider zone is by males ($pmale_{cyclist}(zone) = 0.70$). This means that an estimated $50 * 0.70 = 35$ cycle commuters are male ($OLC_m = 35$) and 15 are female ($OLC_f = 15$).

Applying the formulae presented previously:

(11)

$$SLC(gendereq)_f = OLC * pmale_{cyclists}(zone) * (1 + \frac{tflow_f}{tflow_m})$$

(12)

$$SLC(gendereq) = 50 * 0.70 * (1 + \frac{200}{300}) = 58.3$$

The increase from 50 cyclists to 58.3 represents an increase of 17% from the observed rate of cycling in total numbers of cyclists. All of these extra 8.3 cyclists are female, giving a new total of 15 + 8.3 = 23.3 female cyclists (and still 35 male cyclists). Gender equality in cycling has been reached, such that an estimated 11.7% of commute trips are made by cycling among both men (35/300) and women (23.3 / 200).

5.3 Go Dutch

The 'Go Dutch' scenario represents the rate of cycling that would occur if people had the same propensity to cycle as the Dutch do, for trips of the same length and hilliness. It is important to note that this is not a 'top down' scenario in which the national level of cycling is set to levels found in The Netherlands. The scenario is 'bottom up' because the proportion of trips being cycled is set per OD pair and the end result for any particular region depends on the local distribution of trip distances. Although the Dutch currently cycle far more frequently than the English for short trips, their propensity to cycle still drops rapidly with distance, with relatively few utility trips being made beyond around 15 km.

Based on these insights, the essence of the 'Go Dutch' scenario is the application of distance decay parameters found in the Netherlands to each OD pair in the study area.

In contrast to *govtarget* and *gendereq* scenarios, *godutch* is unrelated to the current rate of cycling. The scenario thus represents the elimination of localised constraints which inhibit cycle use more in some area than others. Local cycle use in *godutch* is therefore constrained only by trip distances and hilliness.

5.4 E-bikes

The aim of this scenario was to provide an indication of the rate of cycling increase possible due to the uptake of electric cycles ('E-bikes'). The scenario represents a reduction in the degree to which cycle use is constrained by trip distances. This is the most ambitious and speculative scenario presented in this paper; it builds on 'Go Dutch'.

The results are based on the decision to increase by a small amount the β_1 distance decay parameter, that corresponds to distance as a linear term. Specifically, we increased this value by 0.025, as we found this to be sufficiently small to avoid generating an implausibly high rate of cycling but sufficiently large to create a noticeable effect. This allows us to illustrate the type of output that will be possible in this model. In future work we plan to update this scenario, basing the changes to the distance decay parameters on real data from the Dutch National Travel Survey. This will build on analysis of the influence of E-bikes on propensity to cycle in the Netherlands that is being undertaken in parallel to the work presented in this paper.

6 Results

To demonstrate how the scenarios work in practice and to provide an overview of the results, Fig. 5 illustrates the observed level of cycling (*OLC*, from the 2011 Census) and the scenario-based level of cycling in two Local Authorities (Manchester and Norwich). Note that while Manchester has a much higher total number of trips than Norwich, the proportion of those trips that are made by cycling is lower. There is noticeable distance decay for all modes of transport, especially for cycle trips in Norwich, where cycle trips above 7.5 km observed from 2011 census data are comparatively rare.

Note that although Manchester and Norwich have very different initial levels of cycling, the final level estimated from the *godutch* and *ebike* scenarios there are similar. This is because trip distance distributions in the two cities are comparable — these long-term scenarios are not influenced by the current rate of cycling. Note also that the *govtarget* scenario in Manchester has a considerably higher rate of cycling than the *gendereq* scenario, whereas in Norwich these scenarios are very similar. This is because Manchester is starting from a lower baseline, so a doubling nationwide results in a relatively high absolute increase in cycling locally. In

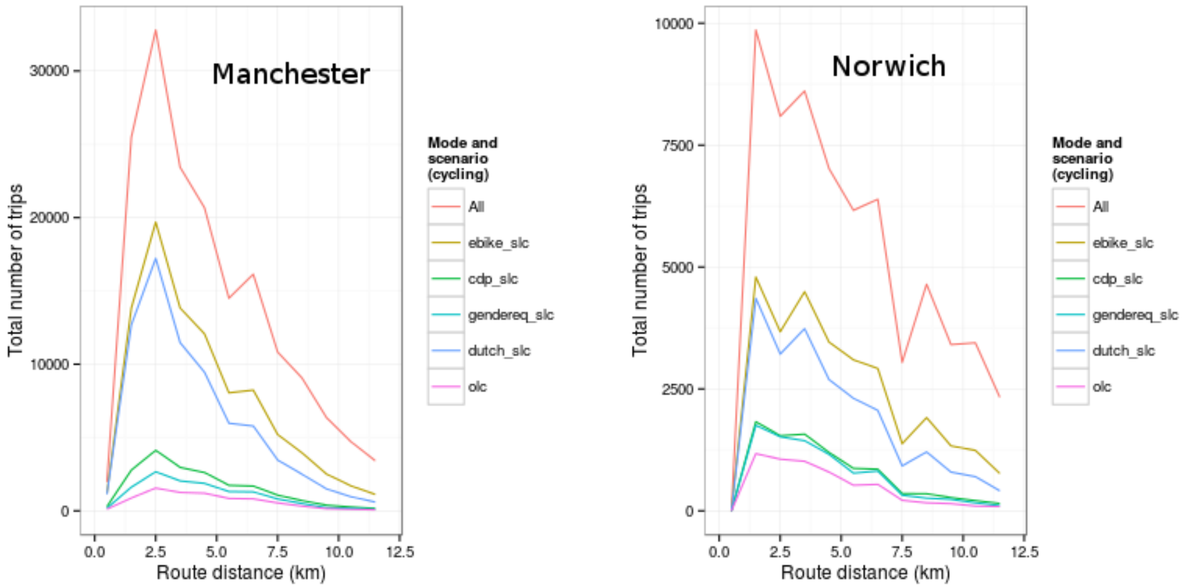

Figure 5: Results of observed and scenario-based levels of cycling from PCT model runs for the city of Manchester (left) and Norwich (right).

Norwich, by contrast, the current rate of cycling is considerably greater than the national average, so the *govtarget* scenario represents less than a doubling in cycling.

The difference between the spatial distribution in cycling potential between the Government Target (*govtarget*) and Go Dutch (*godutch*) scenarios is illustrated in Fig. 6 for Norwich. Note that the top 20 OD pairs in Norwich under *govtarget* assumptions are dominated by the current rate of cycling, with the most travelled desire lines projected to continue to be found towards the east of the city (this can be explained by the location of the University of East Anglia to the east of the city). Under *godutch* assumptions, by contrast, the pattern of cycling shifts substantially to the west. The cycling patterns under the *godutch* scenario are more representative of short-distance trips across the city overall. In both cases the desire lines are focused around Norwich city centre: the region has a mono-centric regional economy, making trips beyond around 5 km from the centre much less likely to be made by cycling.

The equivalent results are shown for the city of Manchester in Fig. 7. This shows that Manchester has a poly-centric structure, favouring the construction of cycle routes between the various sub-centres, not just in radial routes to a single centre. Note in both scenarios the large increase in the level of cycling between *govtarget* (which represents only a doubling nationwide) and *godutch* scenarios (which represents a more ambitious plan for cycling uptake).

As described earlier, Cyclestreets.net was used to allocate OD pairs to the travel network. 'Fastest' and 'quietest' routes were estimated by the service and the difference between these routes can be important from a transport planning perspective. Fig. 8 illustrates this by showing route in Manchester with the highest cycling potential under the *govtarget* scenario. The 'quietest' route is substantially further, with a distance of 2.8 km (as shown by clicking on the line). The 'fastest' route is more direct (with a route distance of 2.3 km) but passes along Trinity Way (the A6042), a busy dual carriage way. The PCT (with the 'Straight Lines' option) tells us that Euclidean distance associated with this OD pair is 1.6 km, resulting in circuity values of 1.44 and 1.75 respectively. We refer to the difference between the 'fastest' and 'quietest' routes as the 'quietness diversion factor' (qdf = 1.2 in this case).

Dutch evidence suggests that cyclists are generally unwilling to take a path that is more than around 1.3 to 1.5 times the length of the 'crow-flies' Euclidean distance (defined as q above). The same research suggests target "for cycle provision should be 1.2" (CROW, 2007). This suggests that high quality cycle infrastructure

Figure 6: Model output illustrating the top 20 most cycled OD pairs in Norwich under Government Target and Go Dutch scenarios.

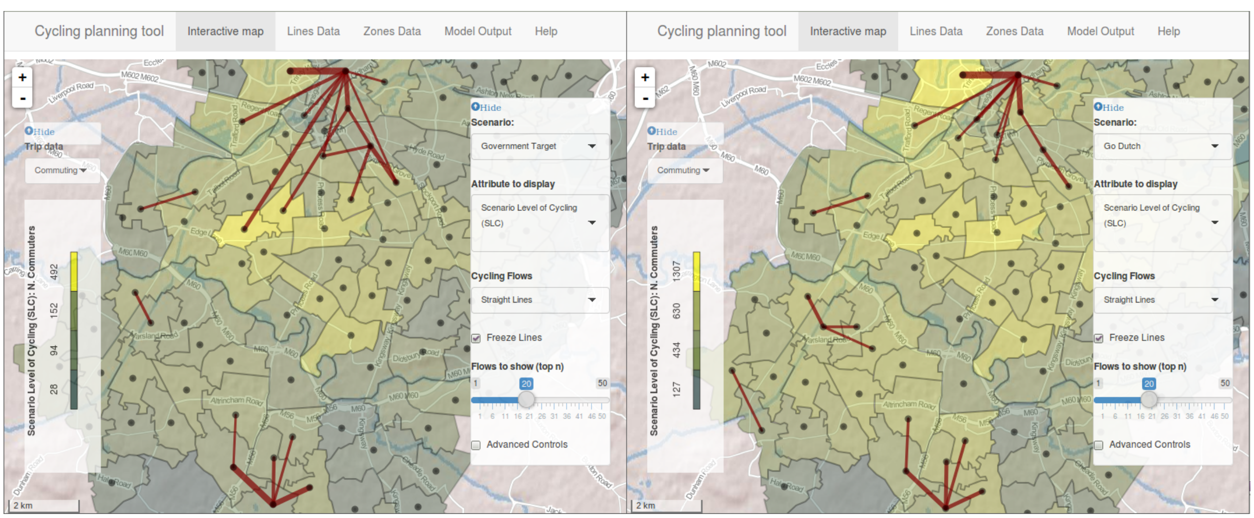

Figure 7: Model output illustrating the top 20 most cycled OD pairs in Manchester under Government Target and Go Dutch scenarios.

along the Trinity Way route would be much better used by commuters than an alternative quiet route that diverges greatly from the shortest path. The decline in cycling propensity with distance supports this approach. The faster decline for women and older people, combined with their greater preference for protected infrastructure, highlights the importance of providing direct and safe routes to encourage cycling amongst groups who currently cycle the least.

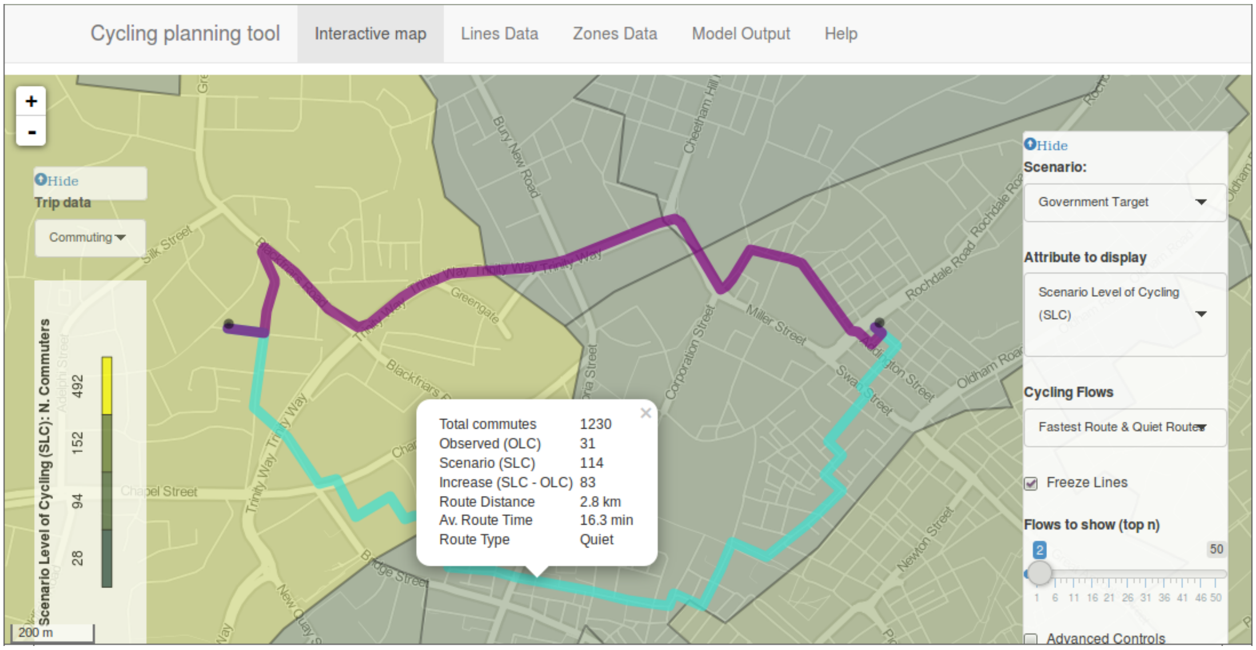

Figure 8: Close-up of the 'fastest' and 'quietest' routes from CycleStreets.net of the OD pair with highest cycling potential under the *govtarget* scenario in Manchester. This provides an indication of the local 'quietness diversion factor'

7 Discussion

The flexibility of the PCT methodology enables its use for applications that go beyond those described in this paper. Because the underlying methods and computer code are transparent and open source, it is possible to use the PCT as a platform for further research and planning applications. This flexibility has been demonstrated by the tool's ability to be deployed in any Local Authority (or other administrative area) in England. Extensibility has been demonstrated by the addition of new scenarios. Three user testing sessions have helped identify shorter-term changes to the interface (such as 'freeze scope') and longer-term needs (such as the use of additional data sources).

Planners can use the different scenarios to consider short, medium, and long-term potential for cycling locally and along specific routes, in combination with local knowledge. In the PCT can therefore shed light on the following question, previously raised by Sloman et al. (2014) and Aldred and Jungnickel (2014): Should cycling investment prioritise areas of relatively low current propensity but high potential, or those of relatively high current propensity but lower potential?

In the Netherlands (representing long-term ambition for cycling), cycling is equally common among males and females. Cycling levels are also even between different socio-economic groups, although ethnic and religious differences exist (Fishman et al., 2015). Demographics should therefore play less of a role in estimating cycling potential for strategic purposes than for identifying 'quick-win' policies based on current propensities. Based on this understanding, the PCT has the ability to represent different scenarios of change. An indication of how the pattern of cycling could shift to new transport corridors in the hypothetical future represented by

'Go Dutch' was illustrated with examples from Norwich and Manchester. These show that as cycling grows, its spatial distribution will shift, to areas with high latent demand. This feature of the PCT was described as 'very useful' by transport planners during user testing, coinciding with the finding that 'visioning' has great potential to improve transport planning for the long-term (Tight et al., 2011).

The results of user testing indicated the utility of online, interactive and open source web applications for cost-effective allocation of investment. Local Authority transport planners working in active travel said that the tool could be useful for setting local targets or implementing locally-specific policies. To follow-up on such feedback, modifications of the methods described in this paper are planned, to help determine the suitability of localised cycling targets in relation to investment options.[9] Moreover, as illustrated by the *govtarget* scenario, the method can be used to translate national targets into local aspirations. However, the implementation of the PCT presented in this paper does have some limitations: the reliance on Census OD data means that the results are not up-to-date; there are no scenarios representing specific infrastructure interventions; and the user interface is constrained to a few discrete scenarios. These limitations open-up the potential for future work, including: using more up-to-date sources of OD data; creating a version of the model to represent the impact of specific improvements to the route network (e.g. by modifying the 'quietness diversion factor', described above); and the implementation of continuous variables to define future scenarios. Wider extensions of the model that could build on the framework presented here include:

- Additional 'output tabs' in the PCT's user interface, to estimate the quantitative benefits of cycling uptake at the local (and potentially route-allocated) level. Benefits estimated could include health savings through increased physical activity to feed into models such as HEAT (Fraser and Lock, 2011). Geographically specific energy and carbon savings of cycling uptake could also be estimated (Lovelace et al., 2011).
- Deployment of the PCT for entire countries. This would depend on having appropriate OD data and could could build on emerging 'Big Data' sources for origin-destination flows (Alexander et al., 2015).
- International comparisons of cycling potential. This could include include an exploration of the relationship between places of high potential and investment. We have already begun this by using Dutch distance decay functions in an English context, but more could be done by fully implementing the model in different country contexts.
- The extension of the model to cover variation between different demographic groups. This could be done using the method of spatial microsimulation, which enables the use of additional individual-level variables, such as access to a cycle, to inform more targeted interventions (Lovelace et al., 2014).
- Additional purposes of trips in the model. An 'education layer' would enable prioritisation of 'safe routes to school', building on methods analysing 'school commute' data (Singleton, 2014).
- The extension of the tool to enable the estimation of cycling demand following new developments, such as high-density housing, a new school or local job creation.

The PCT's open source licence allows others to modify it for their own needs. We actively encourage practitioners to 'fork' the project (Lima et al., 2014), to modify the scenarios, input data and display of the results to suit local contexts. This could, for example, help to visualise city-level targets for the proportion cycling by a certain year and which will vary considerably from place to place in ways not yet well understood. Modifying the code base would also allow transport planners to decide on and create the precise set of online tools that are most useful for their work. Building on participatory models at the macro-level (Macmillan et al., 2014), extensions to the model could include using the PCT methodology to enable public engagement in the strategic planning process around sustainable transport.

Transport policy is a complex and contested field (Banister, 2008). Therefore policy, politics, leadership and vision are key ingredients for sustainable urban mobility that computer models alone cannot provide (Melia,

[9]Targets have proliferated in recent years. For instance, an official target to reach 10% of trips made by bicycle has been made by authorities in Dublin, Leicester and across all of Scotland over various time-scales (Beatley, 2012). A mode share of "20% by 2020" has been set for several cities including San Francisco and Orlando.

2015). The approach described here can assist in this wider context by providing new tools for assessing the best available evidence. The PCT thus supports informed and open decision making. A more specific limitation of the PCT is its current lack of inclusion of detailed cycle route quality data (e.g. width and bumpiness of path), which could help planners assess the scale of changes needed to enable substantial uptake. Future versions of the tool could make use of data derived from new network assessment technologies (Joo and Oh, 2013).

The flexibility of the approach outlined in this paper means that PCT can be seen not only as a tool but as a framework for strategic transport planning. Under this interpretation the case study of cycling in England is just one of many potential applications. Still, a number of the lessons learned throughout the development and user testing of the tool are generalisable internationally. Indeed, one of the major motivations for writing this paper is to showcase the method for use by others to avoid 'reinventing the wheel' to solve such a ubiquitous and embedded problem as the un-sustainability of current travel patterns.

Future work will focus on enabling practitioners to add new features to the PCT. This is based on the understanding that the people who best understand the requirements of transport planners are the transport planners themselves. By reducing barriers to entry in scenario-based transport modelling, the PCT methodology can empower decision-makers, planners and citizens to supplement their understanding of transport systems with evidence and plausible visions of the future.

The PCT is highly policy relevant. By identifying specific routes where intervention is expected to be most effective, it can help to build business cases for further investment and policy change. Moreover, by highlighting the importance of 'arterial' routes to key destinations, the PCT can help rejuvenate long-standing debates such as the re-allocation of road space away from private cars (Black et al., 1992; Jones, 2014; Sharples, 2009). In conclusion, new tools such as the PCT can inform the decision of where to construct new cycling infrastructure and, more widely, strengthen the evidence-base needed for a transition towards sustainable transport systems.

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